Predicting Residential Heating Energy Consumption and Savings from Known Energy Characteristics and Historical Energy Consumption

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Overview

Cost effective retrofits of residential buildings could yield annual electricity savings in this sector of approximately 30 percent in the United States. Furthermore, investment in energy efficiency can create millions of direct and indirect jobs throughout the economy for manufacturers and service providers that supply the building industry. Unfortunately, the actual energy savings, compared to predictions based upon physical energy models, have been somewhat disappointing, leading to wariness on the part of those wishing to invest in efficiency projects. Key to this study will be the use of a large number of buildings/residences for which all energy characteristics are known. The specific case considered here involves hundreds of university-owned student residences in the U.S. Midwest. A neural network approach is used to develop a single model that accurately predicts heating energy for all houses given the specified energy characteristics. The resulting neural net is used to predict savings associated with a small subset of houses in the study which have already been upgraded from a variety of measures. The estimated savings are compared to the actual savings realized. The results show that predicted savings match the actual savings within 2.5 percent for most of the measures considered. These results show the potential for establishing larger public databases of building energy characteristics in order to strategically implement energy reduction strategies with the greatest energy savings per cost to implement.

Problem

- Energy model based estimations of savings from energy efficiency upgrades most often over-predict savings.
- The qualifications of energy modelers are often suspect.
- Building geometry data is generally available from government maintained real estate records.
- Building inspections could and should be used to document residential building energy characteristics.
- Energy consumption data is generally not available but there is increasing pressure to make the energy effectiveness of buildings public.
- Data based models offer an opportunity to predict savings based upon actual data, not inexact models.

Methodology

- In the summer of 2015 energy and building data audits were completed on a total of 139 residential homes that were vacant.
- A Random Forest regression tree approach is used to identify the building geometry and energy characteristics (predictor variables) that most strongly affect energy consumption.
- An Artificial neural network (ANN) model was developed using: building geometry and energy characteristics, energy consumption, and weather data to predict monthly and annual natural gas energy consumption for all residences in the study based upon building geometry and energy characteristics, energy consumption, and weather data.
- Savings from specific upgrades were estimated using the developed model.
- Predicted savings for discrete savings measures were validated by comparing predicted consumption for upgraded residences to existing higher efficiency residences using the k-nearest neighbor method (KNN).

Table 1 .The data used in ANN model constriction

Variable	Input	Output
Floor area (ft^2)	X	
Attic area/ R_{attic} (BTU/hr-°F)	X	
Window area/ R_{win} (BTU/hr-°F)	X	
Wall area/ R_{wall} (BTU/hr-°F)	X	
Furnace efficiency (%)	X	
Energy factor for water heater	X	
Baseline electric intensity (kWh/ft^2)	X	
Number of occupants	X	
Heating slope gas (BTU/hr-°F-ft^2)	X	
Heating balance point temperature (°F)	X	
Average monthly outdoor temperature (°F)	X	
Monthly natural gas usage (ccf/month)		X

Results

Figure 1. Comparison of actual and predicted natural gas consumption for a random sampling of houses for the October 1 – April 1 study period.

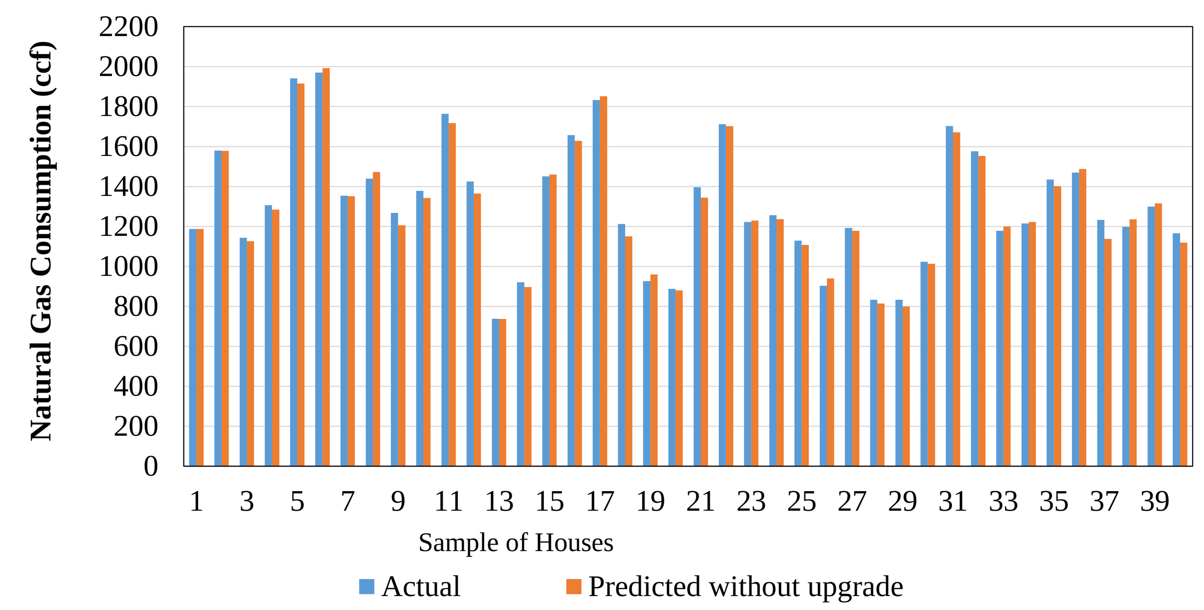


Table 2. Energy effectiveness upgrade characteristics.

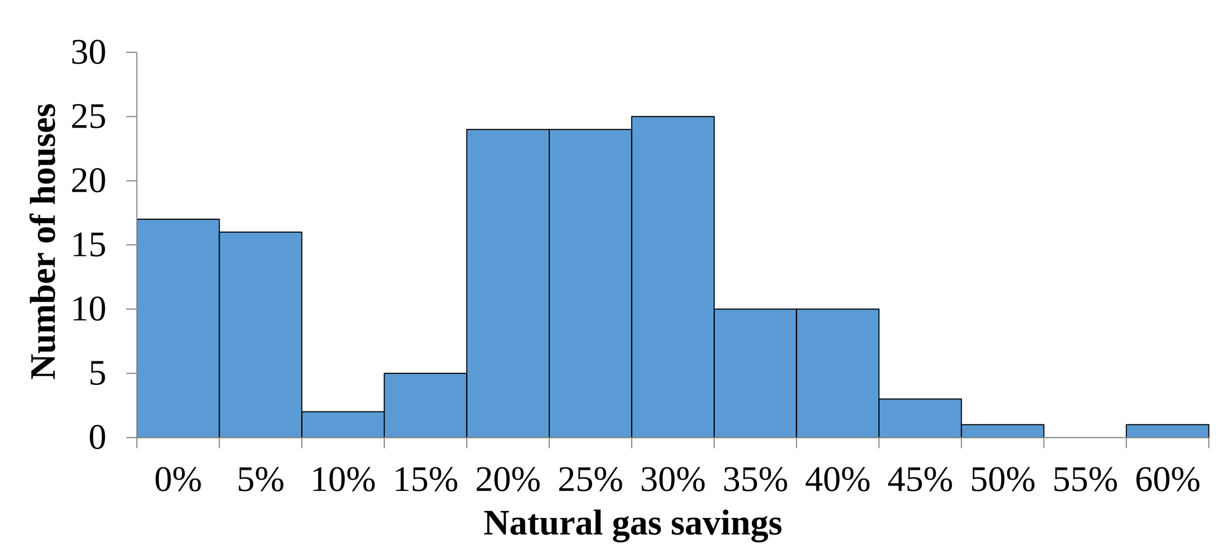
Variable		Input
R_{attic} (hr-ft^2-°F/BTU)		40
R_{win} (hr-ft^2-°F/BTU)		3
R_{wall} (hr-ft^2-°F/BTU)		13
Furnace efficiency (%)		95%
Energy factor for water heater	Instant	0.96
	Storage	0.70
Heating slope gas (BTU/hr-°F-ft^2)		Calculation

➢**Potential energy savings from an individual measures**

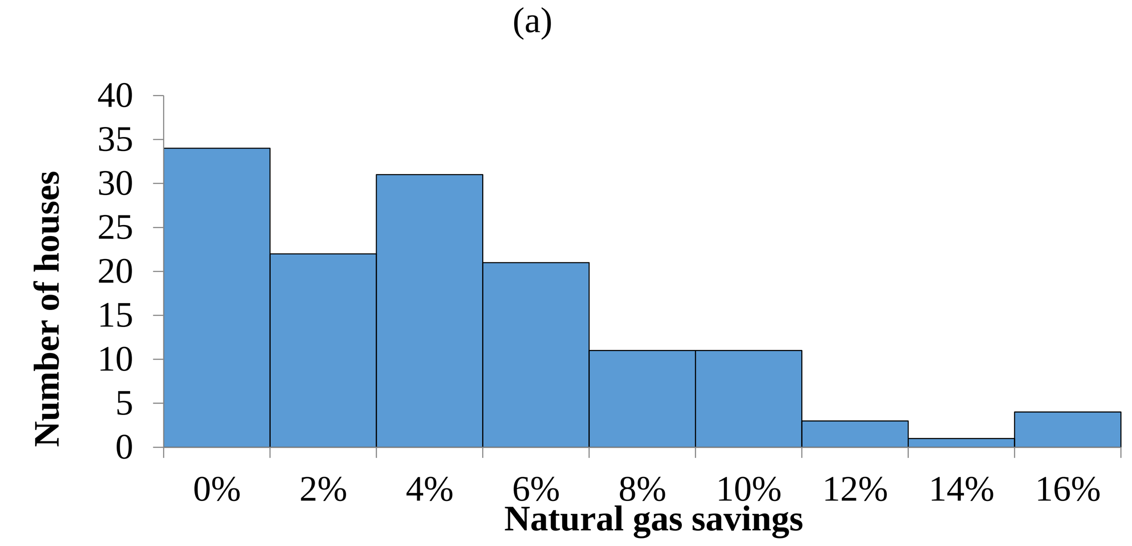
Table 3. Average percentage gas consumption savings from retrofit individual measures

Variable	R_{wall}	R_{attic}	R_{window}	Furnace efficiency	Energy factor water heater
Average percentage gas consumption savings	21%	3%	4%	2%	1%

Figure 2. Histograms of percentage gas consumption savings across all houses from each of the individual measure during winter season for: (a). wall insulation; (b). attic insulation; and (c). furnace efficiency upgrades (%)

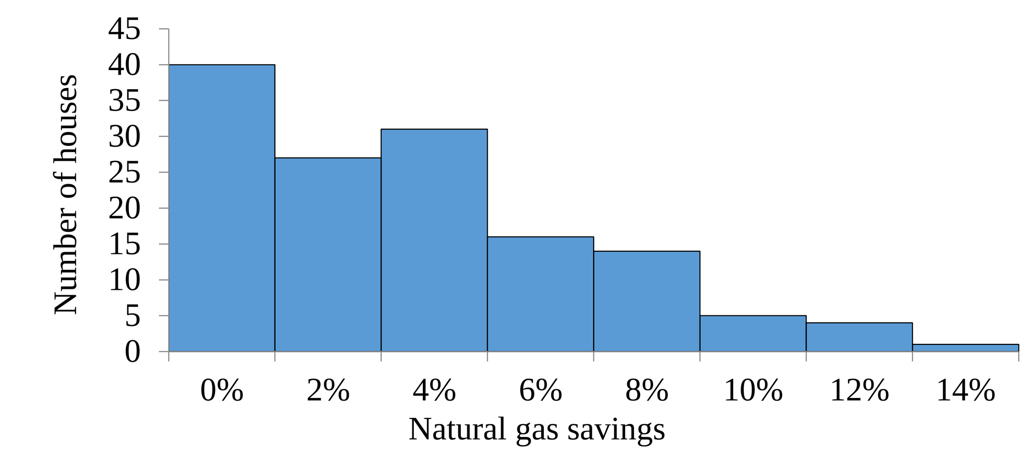


(a)



(b)

Results



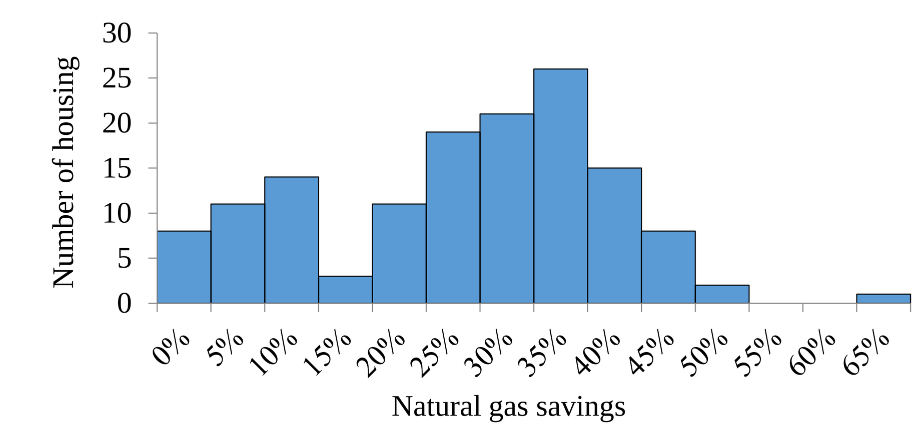
(c)

➢**Potential energy savings from a collective grouping of retrofit measures**

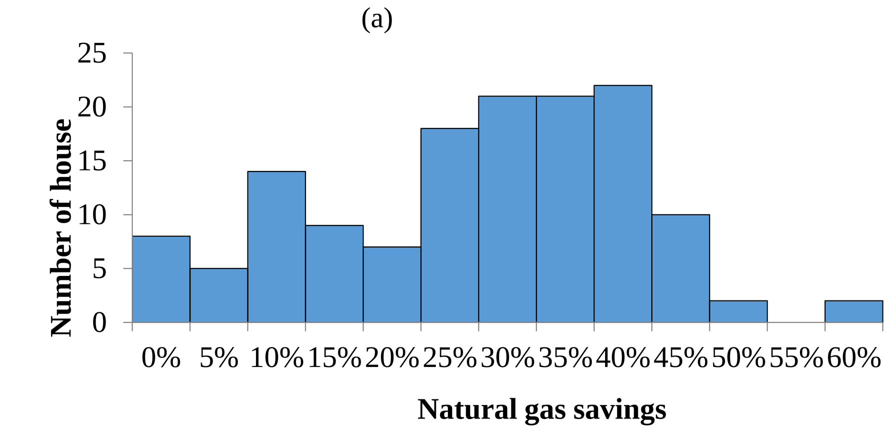
Table 4. The average percentage savings natural gas usage (ccf) from retrofit collective grouping of measures.

Variable	Envelope upgrade	Envelope and furnace upgrade	Envelope, furnace, and water heater upgrade
Average percentage gas consumption savings	26%	27%	27.23%

Figure 3. Histogram of percentage gas consumption savings from among all houses from all energy efficiency measures during winter season for: (a). envelope upgrade; and (b). envelope and furnace upgrade.

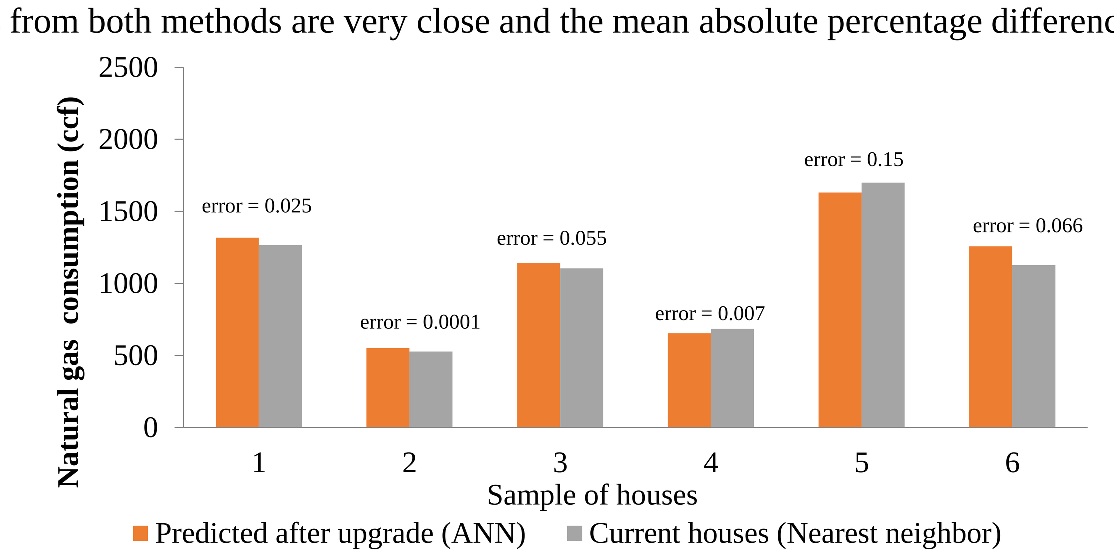


(a)



(b)

Figure 4 illustrates comparison between the results from ANN model with K-nearest neighbor approach to predict the energy usage for six houses include higher and lower energy consumption. The ANN approach to predict savings compares very closely to the energy consumption of the nearest neighbor residence. The results from both methods are very close and the mean absolute percentage difference is 5%.



Conclusion

A machine-learning (artificial neural network) approach is a useful tool for predicting energy savings from retrofit projects. The ANN model developed in the present study is based on a back-propagation algorithm. The inputs of the ANN model for training and testing are considered as A_{floor}, A_{wall}/R_{wall}, A_{attic}/R_{attic}, and A_{window}/R_{window}, the heating temperature balance point temperature, $T_{balh,gas}$, the heating slope, HS_{gas}, baseline electric intensity, and the monthly average outdoor temperature. The coefficient of correlation of the ANN model between the ANN model output and real data is 0.989 and the mean absolute percentage error is 2.5%. The results also show the possibility of accurately utilizing the developed neural net to predict savings for specific energy efficiency upgrades, with predicted consumption for a small set of houses matching to within 5% of the actual consumption in houses identified as nearly identical to the improved house.